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Systemic risk among European banks: A Copula Approach

Jacob Kleinow^a, Fernando Moreira^b

^a *Department of Finance, Freiberg University, D-09599 Freiberg, Germany*

^b *Business School, University of Edinburgh, EH8 9JS Edinburgh, UK*

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Abstract:

This paper investigates the drivers of systemic risk and contagion among European banks. First, we use copulas to estimate the systemic risk contribution and systemic risk sensitivity based on CDS spreads of European banks from 2005 to 2014. We then run panel regressions for our systemic risk measures using idiosyncratic bank characteristics and country control variables. Our results comprise highly significant drivers of systemic risk in the European banking sector and have important implications for bank regulation. We argue that banks which receive state aid and have risky loan portfolios as well as low amounts of available liquid funds *contribute* most to systemic risk whereas relatively poorly equity equipped banks, mainly engaged in traditional commercial banking with strong ties to the local private sector, headquartered in highly indebted countries are most sensitive to systemic risk.

Keywords: SIFI, copula, interconnectedness, bailout, default, CDS, Europe, contagion

JEL Classification: G21, G28, G33

1 Introduction

Which factors determine the interconnectedness of European banks? In this paper, we investigate the drivers of contagion and systemic risk among European banks using a large bank dataset with CDS quotes from 2005 to 2014. Banking *contagion* – a widely debatable issue – refers to the transmission of a bank shock to other banks or the financial system. It lies at the heart of *systemic risk*. Contagion is defined as a significant increase in cross-market linkages after a shock measured by the degree to which asset prices move together (Dornbusch et al., 2000). Early, Bagehot (1873) diagnoses that “in wild periods of alarm, one failure makes many, and the best way to prevent the derivative failures is to arrest the primary failure which causes them”. To this end, we propose two novel measures of systemic risk through contagion using copula functions and credit default swap (CDS) data to capture the systemic impact a single bank default has on the banking system (later *systemic risk contribution*) and vice versa (later *systemic risk sensitivity*). The topic of our paper is of considerable interest to regulators and economists as well: Our results offer new insights into the drivers of financial instability and provide implications for the macroprudential regulation of banks.

Financial systems as a whole tend toward instability. This is due to the fragile nature of their players, especially banks. Because of their role as a financial intermediary (or delegated monitor), their opaqueness, their interconnectedness, and the typical characteristics of their lenders, banks are particularly prone to affecting other banks with financial distress – or to being affected by them. Consequently, the identification of drivers of distress of systemically important banks (SIBs) is of vital importance. Recent papers on contagion among banks produced substantial findings. Dornbusch et al. (2000) and Acemoglu et al. (2015), among others, argue that financial contagion can be ambiguous: As long as the magnitude of negative shocks affecting financial institutions is sufficiently small, a more densely connected financial network (corresponding to a more diversified pattern of interbank liabilities) enhances financial stability. In this paper, however, we do not look at the network structure of interbank markets itself but focus on *systemic default contagion*. Existing literature in this field is comparably young and leaves questions unanswered: (1) First, it is unclear which channels of contagion systemic banking crises have. (2) Second, there is no consensus on how to identify systemically important banks. (3) Third, it is unknown how to measure the potential negative impact those banks can have on the financial system. We contribute to fill in these research gaps by proposing innovative key indicators to measure the extent to which single banks impact on the banking system and vice versa, as well as controlling for determinants of those contagious procedures. This is carried out as follows:

Section 2 offers a review of related literature on contagion and systemic risk (in Europe) as our background and starting point. The subsequent section presents our copula-based model to estimate systemic risk using CDS quotes. The bank selection and data collection are explained in Section 4. In the fifth section, we derive key determinants of contagion in the banking sector, while Section 6 concludes our findings.

2 Related Literature

In this section, we briefly discuss the related theoretical and empirical literature on using copulas for estimating contagion and identifying drivers of systemic risk in the European banking sector. Dornbusch et al. (2000) and Acemoglu et al. (2015), among others, argue that the ways in which bank shocks are transmitted do seem to differ, and these differences are important. We follow their line of thought and propose two novel measures of systemic risk.

The first step for the identification of drivers of systemic risk is the assessment of *systemic risk levels*. The number of measures for systemic risk is growing fast¹. The existing literature can be divided into the (1) *systemic risk sensitivity*- and the (2) *systemic risk contribution* stream. Approaches for (1) *systemic risk sensitivity* (Acharya et al., 2011; Brownlees and Engle, 2012; Jobst and Gray, 2013; Weiß et al., 2014) try to determine systemic importance by measuring the extent to what a single institution is affected in case of a systemic macroeconomic event (e.g. interest rate change); see *Figure 1*. The overall functioning of the (financial) system and individual institutional resilience is in the focus of this first approach². Conversely designed measures dealing with the (2) *systemic risk contribution* (Chan-Lau, 2010; Adrian and Brunnermeier, 2011; Billio et al., 2012; León and Murcia, 2013) try to determine systemic importance by measuring the impact of a negative shock in a single institution on systemic risk³. These measures assess how one institution affects a group of others; see *Figure 1*. According to this understanding, it is of special interest to avoid and mitigate contagion effects.

[Insert Figure 1 here]

¹ Bisias et al. (2012) provide a survey of systemic risk measures. Dornbusch et al. (2000) divide the empirical measures of contagion into the following categories: correlation of asset prices, conditional probabilities, and volatility changes.

² Examples are Marginal Expected Shortfall (MES), SRISK (the capital that a firm is expected to need in financial crises), Lower Tail Dependence (LTD) and Contingent Claims Analysis (CCA).

³ Examples are ΔCoVar , Co-Risk, and Granger Causality.

Copulas (see definition in Section 3.1 ahead) have been applied in different ways in the context of systemic risk. Engle et al. (2014), for instance, use a particular copula (Student t) to represent the dependence across innovations of errors in a GARCH model related to firms' and regions' stock returns. CDS are increasingly used as a proxy for credit risk. Oh and Patton (2013) propose the use of multivariate copulas to model the relationship among CDS spreads and to estimate the CDS issuers' joint probability of distress which is presented as proxy for systemic risk. Martínez-Jaramillo et al. (2010) join individual banks' loss distributions by means of copulas and generate a univariate loss distribution for the whole financial system. Based on this distribution, the authors use risk measures, such as the Conditional Value-at-Risk (CoVaR or Expected Shortfall), to evaluate the system's risk. Philippas and Siriopoulos (2013) study the contagion among six European bond markets by applying bivariate (Student t) copulas with time-varying parameters to model the association across bond returns. Buhler and Prokopczuk (2010) use a particular copula ("BB7") to model the dependence across stock returns in several industry sectors and in the banking sector.

We use CDS prices rather than stock returns as a measure of contagion for one major reason: Unlike CDS, stock prices capture more than the default probability but current and future levels of economic activity (Grossman and Shiller, 1981). Market participants' perception of the value of the assets of a certain issuer may be insightful, but we believe that the pure assessment of default risks and how they ultimately spread gives a clearer idea of contagion and systemic risk among financial institutions.

To sum up, the literature related to the application of copulas in systemic risk investigates the relationship among financial variables (e.g. stock returns and CDS spreads). At this point our study innovates by considering the financial institutions' probabilities of default as the variable of interest and by exploring a novel link between this variable and copula functions. Whereas previous works assume the copula to be used (e.g. Engle et al., 2014; Philippas and Siriopoulos, 2013; Buhler and Prokopczuk, 2010), we estimate the *best-fit copula* for our data using goodness-of-fit tests⁴. This represents an advantage of our study since we select, among some theoretically justified candidates, the empirically most suitable copula for each specific data analysed whilst copulas previously assumed, as done in other studies, might not represent the data considered.

The second step for the identification of drivers of systemic risk and contagion is to run panel regression analyses on our systemic risk results with different potential factors from the micro or macro level that may affect systemic risk. Previous papers came to following findings:

⁴ Genest et al. (2009) provide a detailed introduction into goodness-of-fit tests.

Starting with the (1) *risk sensitivity approach* Engle et al. (2014) find that banks account for approximately 80% of the systemic risk in Europe, with UK and French institutions bearing the highest levels of systemic risk. Acharya and Steffen (2014) come to the conclusion that banks' sovereign debt holdings are major contributors to systemic risk. Vallasca and Keasey (2012) spot several key drivers of systemic risk of European banks like high leverage, low liquidity, size and high non-interest income. Varotto and Zhao (2014) confirm the positive impact of size and leverage on systemic risk for a set of European banks. Black et al. (2013) confirm that bank size has a positive impact on the increase of systemic risk. Interestingly they also find that European banks with a more traditional lending business and more liquid assets are less likely to increase systemic risk. Lastly, they find that bank profitability has no impact on systemic risk and the market to book ratio has an unstable influence on banks' systemic risk in Europe.

Based on the (2) *systemic risk contribution approach* several findings have been made: Bori et al. (2012) detect market based variables as strong predictors for systemic risk in Europe. Their results show that institutional factors like size and leverage contribute significantly to banks' systemic risk. Also the banking system concentration increases systemic risk. Hautsch et al. (2014) find that unlike leverage and funding risk (measured by maturity mismatch), size is not a dominant factor among European banks.

The empirical literature on systemic risks of European banks, however, still lacks a comparative study that examines the drivers of systemic risk of banks derived from CDS quotes (default contagion). In addition to closing this research gap we combine this with a broad set of bank characteristics and country policy variables.

3 Measuring systemic risk and contagion

To measure systemic risk and contagion in the European banking system, we propose new risk measures, systemic risk *sensitivity* and systemic risk *contribution* controlling for the two channels of contagion illustrated in *Figure 1* by combining the interpretation of default in *structural credit risk models* and *copula functions*. The first measure captures the potential impact of a banking system's distress on each financial institution and the second measure captures the potential impact of an institution's failure on the banking system. To analyse the determinants of systemic risk, we make use of the approaches elaborated by Acharya and Steffen (2014), and Weiß et al. (2014).

3.1 Copulas

Copulas are functions that link univariate distributions to the multivariate distribution of the related variables:

$$H(x, y) = C(F_X(x), F_Y(y)) \quad [1]$$

where C is the copula, $H(\cdot)$ is a bivariate function, and $F_X(\cdot)$ and $F_Y(\cdot)$ are cumulative distribution functions of X and Y , respectively.

Due to the “Probability Integral Transformation”, $F_X(x)$ and $F_Y(y)$ represent variables uniformly distributed in $(0,1)$. That is, whenever a random variable is evaluated in its own continuous cumulative distribution function (F), all the resultant values are equally spread in the interval between 0 and 1 (Casella and Berger, 2008).

So, the copula C links uniform variables, $F_X(x)$ and $F_Y(y)$, to a multivariate distribution that, in this example, gives $\Pr[X < x, Y < y]$, the probability that X and Y are simultaneously below x and y . Such uniform variables correspond to the quantiles of the distributions F_X and F_Y respectively evaluated at x and y . Thus the dependence measured by copulas is valid for any type of distribution.⁵

The likelihood of a variable being below a specific value conditional on another variable being below another particular point can also be calculated by means of copulas. The probability that X is smaller than x conditional on Y being smaller than y can be found by the expression:

$$\Pr[X < x \mid Y < y] = \frac{\Pr[X < x, Y < y]}{\Pr[Y < y]} = \frac{C(F_X(x), F_Y(y))}{F_Y(y)} \quad [2]$$

where the notation follows [1] and the symbol “|” stands for “conditional on”.

3.2 A Copula approach to estimate conditional default

3.2.1 Structural interpretation of probability of default

In this paper, the use of copulas to estimate joint defaults relies on a basic assumption of structural credit risk models (initially proposed by Merton, 1974) according to which an obligor defaults when a latent variable (typically interpreted as the log-return of an obligor’s assets) falls below a threshold (the amount needed to pay the outstanding debt). So, if the latent variable is denoted as Y and its cut off value (below which default happens) is y_c , the highlighted area in Figure 2 represents the probability of default (PD).

⁵ For an introduction and more details about copulas, see Nelsen (2006) and Joe (2014).

[Insert Figure 2 here]

To measure contagion we start with the estimation of the probability that two obligors i and j default at the same time: In credit risk models largely employed by industry nowadays⁶, this likelihood is estimated in line with factor models which assume that the correlation among defaults is driven by the debtors' latent variables (e.g., Bluhm et al., 2010; Crouhy et al., 2014). These models have the limitations of assuming *normally-distributed variables* (which in general does not correspond to the reality in financial markets) and using the *linear correlation* (which is not an adequate measure of dependence when variables diverge from the normality – see Embrechts et al., 2002).

Given that the probability of default can be associated to a distribution function (of latent variables), copulas can be used in this context to model the dependence across the latent variables (regardless of their distribution shape) so that the distributions F_X and F_Y in expression [2] result in probabilities of default.

3.2.2 The model

Following structural credit risk models, it can be assumed that the observed PD of a particular financial institution, *bank*, is the probability that an underlying variable (e.g. its liquid assets) will fall below a specific level (equivalent to the e.g. short-term liabilities). It is not possible to distinguish which proportion of this potential failure is resultant from the default of other financial institutions (i.e. a systemic risk event/systemic shock) and which part is caused by the respective bank's individual characteristics.

To this end we calculate the probability of default of an individual *bank* at time t conditional on a systemic crisis in the banking *system* at time t : This can be achieved by estimating the joint probability of default (*joint PD*) of the bank and the banking system. This *joint PD* can be estimated via copulas. Based on [2] the probability of an individual bank default at time t ($PD_{bank,t}$, the probability of its latent variable $Y_{bank,t}$ falling below a threshold $y_{bank,c,t}$ at time t) conditional on a systemic crisis ($PD_{system,t}$, similarly, the probability of $Y_{system,t} < y_{system,c,t}$ at time t) is given by the copula that links those two variables evaluated at the cut off points divided by the probability of a systemic crisis:

$$Pr[Y_{bank,t} < y_{bank,c,t} | Y_{system,t} < y_{system,c,t}]$$

⁶ Popular examples of quantitative credit analysis are Moody's KMV (KMV, 1987) model and JP Morgan's CreditMetrics (JP Morgan, 1997).

$$= \frac{\Pr[Y_{bank,t} < y_{bank,c,t}, Y_{system,t} < y_{system,c,t}]}{\Pr[Y_{system,t} < y_{system,c,t}]} = \frac{C(F_{Y,bank}(y_{bank,c,t}), F_{Y,system}(y_{system,c,t}))}{F_{Y,system}(y_{system,c,t})}$$

Since, for each bank, $PD = \Pr[Y < y_c] = F(y_c)$, the expression above becomes:

$$\begin{aligned} PD_{bank|system,t} &= \Pr[Y_{bank,t} < y_{bank,c,t} | Y_{system,t} < y_{system,c,t}] \\ &= \frac{\Pr[Y_{bank,t} < y_{bank,c,t}, Y_{system,t} < y_{system,c,t}]}{F(y_{system,c,t})} \\ &= \frac{C(PD_{bank,t}, PD_{system,t})}{PD_{system,t}}. \end{aligned}$$

Thus, we can write:

$$PD_{bank|system,t} = \frac{C(PD_{bank,t}, PD_{system,t})}{PD_{system,t}}. \quad [3]$$

This means that the probability of default of *bank* at time t conditional on the failure of the banking *system* ($PD_{bank|system,t}$) will be given by the copula that associates the probability of default of the *bank* at time t with the probability of a banking *system* default at time t divided by the banking *system*'s probability of default at time t . This method has the advantage of capturing possible higher impact of the banking *system*'s failure on a *bank* when their probability of default is higher (e.g. in downturns). Alternatively, lagged data concerning the banking *system* ($PD_{system,t-1}$) that might trigger the default of other institutions can be used.

According to [3], if $PD_{bank,t}$ increases and $PD_{system,t}$ remains constant, $PD_{bank|system,t}$ either increases (likely) or does not change (as the copula C may remain constant due to small increments in $PD_{bank,t}$). On the other hand, if $PD_{system,t}$ increases and $PD_{bank,t}$ remains constant, the change in $PD_{bank|system,t}$ calculated in [3] depends on how much $C(PD_{bank,t}, PD_{system,t})$ and $PD_{system,t}$ change. The same applies to situations where both $PD_{bank,t}$ and $PD_{system,t}$ increase.

It is interesting to note that the copula C refers to the dependence across the latent variables (Y) but data on probability of default (PD) can be used to estimate that copula. Since copulas are invariant under strictly increasing transformations of variables (Embrechts et al., 2002) and PD is a strictly increasing transformation of the latent variables⁷, i.e. $PD = F(y)$, the copula between PD s is identical to the copula between Y s. Thus, to find this copula the observable PD information has to be used. Once the copula that links PD s is identified it can be used to connect the underlying variables. A numerical example (Table 1) elucidates the steps to estimate the *bank*'s probability of default depending on the failure of the banking *system*. Table 1 (partially) displays some hypothetical values of PD s (in decimal format) for a

⁷ That is, the smallest PD is associated to the smallest y and so on until the highest PD which is associated to the highest y .

bank and for the banking system, over a period of T months (naturally, other periods, such as weeks, could be used).

By using [3], we can estimate the conditional PD involving the *bank* and the banking *system* for each period. At this point, we will have a *bank*'s probability of default conditional on the systemic event in the banking sector ($PD_{bank/system}$) for each month so that we will have a set of T values (since the dataset covers T months) – see Table 1.

[Insert Table 1 here]

Hence, in sum, to estimate *bank*'s probability of default conditional on the failure of the banking *system* we follow a four-step procedure: First, we select candidate copulas to represent the dependence between PD_{bank} and PD_{system} (note that lagged observations of the conditioning banking *system* can be used). We then use a Maximum Likelihood (ML) method to estimate the best-fit parameter (θ) for each candidate copula (e.g., Joe, 2014). After that, considering the parameters found in the previous step, we apply a goodness-of-fit test to decide which copula is the best representation of the dependence structure of the observed data (Berg, 2009; Genest et al., 2009). Finally, after finding the best-fit copula family (e.g. Gaussian or Gumbel) and its respective parameter (θ), we use expression [3] to calculate $PD_{bank/system,t}$ for each period t (month t in the example shown in Table 1). This will yield a conditional probability of default for each period.

Similar to [3], the probability of a systemic crisis in the banking *system* at time t conditional on the default of a particular *bank* at time t ($PD_{system|bank,t}$) is given by:

$$PD_{system|bank,t} = \frac{C(PD_{system,t}, PD_{bank,t})}{PD_{bank,t}}. \quad [4]$$

4 Data

In this section we explain the sample selection and data collection.

4.1 Sample selection and CDS data

We start by selecting the ten year period 2005-2014 for our analysis. It is the largest available sample of CDS prices of European financial institutions and covers tranquil times 2005-2007 as well as periods with turmoil during the “great financial crisis” (GFC) and with turbulent developments among the European (sovereign debt) market 2008-2014 (Black et al., 2013).

Subsequently, to have a testable sample of systemically relevant banks in the European Union, we choose the 2014 European Banking Authority (EBA) EU-wide stress test sample of banks as it includes quantitative and qualitative selection criteria. The bank selection is based on asset value, importance for the economy of the country, scale of cross-border activities, whether the bank requested/received public financial assistance⁸. This initial EBA-sample contains 124 bank holdings from 22 countries⁹. We start collecting data for CDS of *senior unsecured* debt with a *maturity of five years* of the banks from the EBA-sample from *S&P Capital IQ*. However, the number of European banks with publicly traded CDS is 47 for the period 2004-2014, leading to 373 observed banks over 11 years. Due to lacking or inconsistent accounting and missing country data, after hand collecting missing values, we further have to exclude a number of banks,¹⁰ so that we finally produce a full (unbalanced panel) sample composed of 260 observations of 36 European financial institutions from 2005 to 2013¹¹. The banks in our final sample are listed in Appendix Table 1. We use daily data to estimate the probability of default (PD) of those institutions (using expression [5] below) from 15 Aug 2005 to 31 Dec 2014¹².

Assume a one-period CDS contract with the CDS holder exposed to an expected loss, EL , equal to: $EL = PD(1 - RR)$, where PD is the default probability, and RR is the expected recovery rate at default.¹³ Neglecting market frictions, fair pricing arguments and risk neutrality imply that the credit default swap (CDS) spread, s , or “default insurance” premium, should be equal to the present value of the expected loss (Chan-Lau, 2006):

$$S = \frac{PD(1-RR)}{1+rf}$$

⁸ The newer, but slightly shorter European Central Bank (ECB) list of “significant” supervised entities from September 2014 equals the EBA 2014 list with a few exceptions. We do not use this list since it does not include UK banks.

⁹ Namely Australia, Belgium, Cyprus, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Luxemburg, Malta, Netherlands, Norway, Poland, Portugal, Slovenia, Spain, Sweden, United Kingdom.

¹⁰ We manually check missing accounting values, finding most of them. In some cases, however, we do not find the necessary data, which may bias our results since balance sheet composition may affect the bank opacity (Flannery et al., 2013). In a recent paper on bank opaqueness, Mendonça et al. (2013) find that a decrease in bank opaqueness fosters an environment favourable to the development of a sound banking system and the avoidance of financial crises.

¹¹ The year 2004 has to be excluded due to non-availability of the overnight index swap rate.

¹² Although the information on CDS spread is available from 01 Jan 2004, the data on the risk-free rate used to estimate probability of default (PD) are only available from 15 Aug 2005. Thus, our sample period to estimate PD starts on 15 Aug 2005 and, as we are using daily data, there are 100 observations in 2005, which are enough for the estimation of the dependence structures (copulas) in that year.

¹³ The recovery rate and default probability are assumed to be independent.

where s is the CDS spread, rf is the risk-free rate, and RR is the recovery rate. The probability of default (PD) of the financial institutions considered is estimated according to the following formula mentioned in Chan-Lau (2013, p. 64):¹⁴

$$PD = \frac{s(1+rf)}{1-RR} \quad [5]$$

Note that RR is restricted to $RR \leq -s(1+rf)+1$ given that $0 \leq PD \leq 1$. Empirical papers find historical recovery ratios for financial institutions of usually 40-60% (Acharya et al., 2004; Conrad et al., 2012; Black et al., 2013). For our baseline regressions we use a recovery rate of 50% ($RR=0.5$) as Jankowitsch et al. (2014) find a mean recovery rate of 0.493 for US banks and Sarbu et al. (2013) find a mean recovery rate of 0.495 for senior unsecured debt of financial institutions in a US/EU sample.¹⁵

In line with a current tendency in the financial industry (Brousseau et al., 2012), the overnight index swap (OIS) rate is used as the risk-free rate. Contrary to London Interbank Offered Rate (LIBOR) swap rates, the traditional benchmark in the past, the credit risk of counterparties in OIS does not affect rates as much and it therefore can be seen as a default-free rate (Hull and White, 2013). Moreover, recent illicit practices by banks to influence the LIBOR rate have contributed to the adoption of an alternative proxy for the risk-free rate (Hou and Skeie, 2014).

The CDS premium of the Europe Banks Sector 5 Year CDS Index (EUBANCD) is used as a proxy for the calculations of the probability of a systemic shock in the European banking system. This CDS index represents a price basket of all bank CDS from Europe and has more than 50 constituents. The other variables were the same used in the calculation of the institutions' PDs.

4.2 Copula Selection

We consider four *candidate copula families* to model the connection between the probabilities of default of the financial institutions analysed: Clayton (lower-tail dependence), Gaussian (symmetric association without tail dependence), Gumbel (upper-tail dependence) and Student t (symmetric association with tail dependence). These families cover the main combinations of features (in terms of symmetry and tail dependence) necessary to capture the possible links between the variables studied and are most commonly used copulas in finance

¹⁴ For earlier studies on CDSs' implied default probability, see e.g. Duffie (1999) as well as Hull and White (2000).

¹⁵ To show that most of our results do not depend on the recovery rate we chose, we provide results for RR s of 0.10, 0.40, 0.60 and 0.90 as a robustness check.

(Czado, 2010). As for goodness-of-fit tests we use the most robust methods according to Berg (2009) and Genest et al. (2009).

The number of best-fit copulas for each of the aforementioned families regarding the association across each financial institution and the banking system is shown in Table 2.

[Insert Table 2 here]

In the case of 30 institutions the *Clayton*-Copula (stronger dependence at lower values of PD, as in the example of HSBC, Figure 3) fits best to explain the default dependence of an institution and the banking system. A relatively high contagion can therefore be expected in relatively stable market periods for those 30 institutions. This result shows that interconnectedness decreases for many European banks in crisis periods, possibly driven by decreasing interbank trading. The Gaussian copula (no dependence in extreme ranges) does not express the dependence regarding any bank in the sample. This result is not really surprising since a symmetrical dependence without strong association in extreme ranges seems to be quite rare. In the case of four of the 36 financial institutions in our sample the Gumbel copula represents the dependence between the probability of default and the probability of distress in the whole system. This indicates right-tail dependence and means that relatively large values of the PDs are more connected than intermediate values of PD. An example is the dependency of the default probability of the Bayerische Landesbank and the European banking system shown in Figure 3. This Gumbel copula means, in other words, that some institutions can get especially risky in times of crises since they amplify the undesired effects of the crisis and the contagion. The dependence regarding 13 of the institutions considered is represented by the Student t copula which means that extreme values of PD (both low and high) are more connected than intermediate values of PDs are, as in the example of Credit Agricole shown in Figure 3

So, as expected, all the institutions considered present tail dependence and 17 of them (those institutions whose dependence with the bank system is characterized by the Gumbel or the Student t copulas) have stronger connection with the system's distress when their probabilities of default are at high levels. Conversely, the other 30 institutions (whose association with the whole system is expressed by the Clayton copula) have stronger association with the bank system when their default probabilities are low.

[Insert Figure 3 here]

4.3 Bank characteristics and country controls

The second purpose of our study is to identify determinants of contagion among banks in Europe. We investigate the extent to which, ultimately, panel regressions of joint default probabilities could explain why some banks have a higher influence on systemic risk than others.¹⁶ With this objective in mind, we collect a dataset on idiosyncratic bank characteristics as well as information concerning countries' regulatory environments and macroeconomic conditions. The data on bank characteristics are obtained from *Thomson Reuters Worldscope*. The full variable definitions can be found in Appendix Table 2. Where available, we fill data gaps manually with data from banks' websites.

[Insert Table 3 here]

To control for the impact of different macroeconomic conditions and regulations among the European Union jurisdictions, we include another three variables. Differences in (capital) regulation are of special interest, because stricter regulations and powerful supervisors could limit systemic risks. The data we use are provided by the *World Bank*, *Eurostat* or *European Commission* databases (Appendix Table 2 provides detailed definitions and data sources). Table 3 also reports the expected influence of the explanatory variables we use in the panel regressions.

5 Results

In this section, we first present the results for the estimates of banks' systemic risk and then turn to the panel regressions of the dependent systemic risk measure for our sample of 260 bank observations during the period 2005 - 2013.

5.1 Systemic risk of European banks

To analyse the determinants of contagion among European banks, we first compute the conditional probabilities $PD_{bank/system}$ and $PD_{system/bank}$ for all banks in the sample following expressions [3] and [4], respectively. The results show that, on average, the highest sensitivity of banks to a potential financial crisis ($PD_{bank/system}$) is observed in 2006 (see Table 4) whilst

¹⁶ Interestingly and in contrast to most of the literature, Dungey et al. (2012) find cases where firm characteristics make little difference to the systemic risks of banks.

the highest risk of collapse of the whole bank system as a consequence of the failure of a single institution ($PD_{system/bank}$) happens in 2008 (see Table 5). The two measures present different behaviour; $PD_{bank/system}$ (our measure of systemic risk sensitivity) increases from 2005 to 2006 and then falls reaching its minimum level in 2009. After that, it oscillates until the end of our sample period in 2014. On the other hand, $PD_{system/bank}$ (i.e. individual's banks' contributions to the systemic risk) decreases between 2005 and 2006. Then it rises until 2008 when its peak is observed. Next, it falls until 2014.

These results indicate that the systemic risk has continuously decreased since the GFC but the sensitivity of individual financial institutions to systemic shocks has oscillated since 2009 with an upward trend in the recent years. This means that, although the probability of a generalised financial crisis resulting from the failure of a single bank has reduced, if such crisis occurs the potential impact on each bank will be, on average, higher than it would have been around five years ago.

However, it is interesting to note that, although the two measures, $PD_{bank/system}$ and $PD_{system/bank}$, present distinct patterns the magnitude of the latter is higher than the magnitude of the former in all years covered in our sample.

[Insert Table 4 here]

[Insert Table 5 here]

5.2 Panel regressions of systemic risk

Turning to our main research question, we try to identify the drivers of contagion among our sample of European banks. To this end, we estimate several linear panel regression models using the annual mean conditional probabilities $PD_{bank/system}$ or $PD_{system/bank}$ as the dependent variables as well as nine bank specific and three country/policy specific explanatory variables: Table 6 presents the results of our main regressions for the 260 bank observations, whilst results of numerous robustness checks follow in Section 5.3 and panel data tests/diagnostics are reported in the appendix.

The random effects estimator is used in order to account for time-variant bank-specific data and guarantees consistent coefficient estimates in the baseline regressions. Further details of the test diagnostics (random effects, (time) fixed effects, cross sectional dependence) are reported in Appendix Table 3. The Hausmann (1978) specification test indicates that the random effects estimator is only consistent for one regression (assumption of $RR=50\%$) in

Table 6, and thus we use the fixed effects estimator model. The rationale behind the fixed effects model is that, unlike the random effects model, variation across banks is assumed to be neither random nor uncorrelated with the predictor or independent variables included in the model. All estimation results of the linear fixed effects panel regression models, are based on Driscoll and Kraay (1998) standard errors because unreported results confirm the presence of heteroskedasticity, autocorrelation and cross sectional dependence in our regressions. We control for time fixed effects by splitting the sample in a stable (2005-2007) and crisis (2008-2013) period sample. Appendix Table 4 provides correlations of the variables used in the regressions.

The panel regression models in Table 6 indicate that numerous explanatory variables have a significant effect on bank contagion. Most resulting coefficients, however, match closely with our estimated direction of the influence, which is derived from theory and existing empirical literature: To start with *NON_PERF* – a proxy for a bank’s loan portfolio quality – is significant for systemic risk contribution during the tranquil period. Our results indicate that a high share of loan loss provisions to the total book value of loans increases systemic risk *contribution* during non-crisis times. The systemic risk *sensitivity*, however, is not affected by loan loss provisions of banks.

A further variable we use is the regulatory measure *TIER1*-ratio (or Basel core capital ratio), which is the ratio of core equity capital to total risk-weighted assets, measuring the capacity of loss absorption. According to regulators, a high *TIER1*-ratio would indicate that the bank is in a solid state and more resilient to external shock. In this case, we would expect it to have a negative impact on a bank’s systemic sensitivity. Our empirical results confirm this for the systemic risk sensitivity during the crisis period. During the tranquil period, however, the coefficient for *TIER1* indicates the contrary: Systemic risk contribution is driven by *TIER1*. Equally from a theoretical perspective Perotti et al. (2011) find that banks that are forced to have a higher regulatory coverage ratio, may be incentivised to take even more risk because they do not internalise the negative realisations of tail risk projects.

As a proxy for the banks’ liability portfolio and business type, we utilise *DEPOSIT*, i.e. the ratio of total deposits to total liabilities. Traditional commercial banks with a focus on non-securitised savings and loan business usually have high deposit ratios. In particular, banks with high deposit ratios are financed less via securities or by the capital market in general. Therefore, they are less connected to other banks or other institutional investors. For these reasons, we expect *DEPOSIT* to have a negative influence on banks’ systemic risk. We cannot confirm this but find a positive correlation of systemic risk sensitivity and the deposit ratio during the crisis period. A high *LEVERAGE* – the ratio of debt to equity – means that a bank is financed to a large extent by creditors, exposing them to high financial leverage risk that is

due to the actions of private depositors in particular. Our results, however, show insignificant coefficients.

Another bank-specific variable we consider is *LIQUIDITY* (the ratio of cash and tradable securities to total deposits): A large portion of cash and security reserves is probably advantageous at times of negative shocks in the financial system, when interbank markets easily dry out and liquidity becomes scarce (e.g. Brunnermeier, 2009). The coefficient indicates that *LIQUIDITY* has a two-sided impact on systemic risk during the crisis period; an outcome that literature and theory do support, as banks with high reserves of liquid assets (e.g. stocks held for trading and other tradable securities) are more vulnerable to market reactions, but contribute less to systemic risk since solvent banks are able to endow sufficient capital and current asset reserves, i.e. cushions against losses or liquidity shortages.

Next, we control for the influence of banks' profitability on systemic risk by employing the capital-oriented return on invested capital (*ROIC*). In principle, as Weiß et al. (2014) argue, *ROIC* could be coincident with stability or risk: High values of *ROIC* could shield from the risk of defaulting, so that those banks could be a pillar of stability. Higher profitability, on the other hand, could also be the result of extended yet successful engagement in risky lending/non-lending activities, which may suddenly cause or contribute to the bank's as well as general systemic instability. This may explain the weak positive effect on systemic risk sensitivity we find.

[Insert Table 6 here]

Our country controls are insightful too: To control for the country's indebtedness where the bank is headquartered we use the external debt ratio (*DEBT*), which is the government gross debt in relation to the respective gross domestic product (GDP). Policy makers in countries with high levels of debt have lower chances to bailout banks since financial resources are scarce. We therefore expect high government debt levels to positively influence domestic banks' systemic risk *sensitivity*. Our empirical results confirm this for the case of the systemic risk sensitivity: The fragility of banks due to systemic events (systemic risk sensitivity) is driven by government indebtedness. Banks in highly indebted countries, however, spread less risk into the banking system, as the negative correlation of *DEBT* and systemic risk *contribution* indicates. To additionally examine to what extent the inter-relations between a country and its domestic banking sector drive systemic risk, we use the claims of the institutions on their respective central government (as a percentage of GDP) as another variable (*CLAIM*). If the domestic banking sector holds a relatively high share of its

government's public debt, this should increase the systemic risk of banks in the financial system. We find mixed results. Another variable to consider is *CREDIT* - the amount of financial resources banks provide to the private sector of their country as a percentage of GDP. If the private sector borrows financial resources on a large scale, banks are probably more systemically relevant since they would call in their loans in times of distress. Our results confirm that assumption for the case of systemic sensitivity. It shows that banks are more likely to be negatively affected by macro shocks when there is a high dependency on the economic well-being of the private sector of a country. Finally, to capture the influence of governmental aid for certain banks on systemic risk, we control for state aid interventions. Interventions only started in 2008. We find that state aid makes banks more resilient towards systemic shocks. The observable decrease of the systemic risk sensitivity due to government interventions is plausible, and intended by regulators. An increase in the systemic risk contribution, as the results show, may be one unintended side effect of the intervention. It can be explained with an increased confidence of market participants that an institution is TBTF.

For each form of systemic risk, we only report two baseline regressions. We estimate further specifications of the panel regressions using different sets of bank-/country-specific variables. Although we do not tabulate all results from these additional regressions, we comment on them in the following Section 5.3, where we analyse the robustness of our results.

5.3 Robustness checks

We perform numerous checks to examine the robustness of our results to alternate model specifications and different data. To show that our results will not change using a different recovery ratio, Appendix Tables 5 and 6 provide robustness check results for the panel regressions (fixed effects) of banks' systemic risk using a recovery ratio assumption of 10% and 90%, respectively. The significant coefficients of the regression model on banks' systemic risk *sensitivity* do not change their direction (positive/negative) of how they affect systemic risk. Only for a recovery rate of 90% results indicate that *CLAIM* and *LIQUIDITY* become insignificant. However, for a recovery rate of 90% *NON_PERF* and *LEVERAGE* have a significant risk decreasing influence. We can further prove that the results of the baseline regressions depend neither on insignificant explanatory variables nor on the choice of a fixed or random panel regression model. Additionally, we estimate alternative specifications of the panel regressions using different sets of explanatory variables. We find that the results from our baseline regressions are not substantially affected. To conclude, our robustness checks generally suggest that the findings obtained in the baseline specifications are robust.

6 Conclusion

In this study, we analyse the major drivers of contagion among banks in Europe. In particular, we explain why some banks are expected to contribute more to systemic events and are more likely to be negatively affected by systemic events in the European financial system than others. In our panel regressions, we find empirical evidence supporting existing literature on bank contagion, identifying the asset/liability structure, loan portfolio risk, and a few macroeconomic conditions as drivers of contagion. We also find that simpler approaches in measuring systemic risk – as proposed by Rodríguez-Moreno and Peña (2013) – would not be suitable because the systemic risk sensitivity and the contribution of a bank to systemic risk are driven by different factors.

Comparably to Acemoglu et al. (2015) our results highlight that the same factors that contribute to resilience under certain conditions (e.g. liquid assets that decrease systemic risk contribution during the crisis) may function as significant sources of systemic risk under others. To point out the major differences between determinants of systemic risk *sensitivity* and systemic risk *contribution*, we find that relatively poorly equity equipped banks, mainly engaged in traditional commercial banking, headquartered in highly indebted countries with strong ties to the local private sector have the highest systemic risk *sensitivity*. We additionally show that systemic risk *contribution* stems from those well equity equipped banks with risky loan portfolios that have low amounts of available liquid funds, receive state aid and are located in countries with lower government debts.

Regulators have to consider a broad variety of indicators for systemic importance. Banks' size and liquidity as well as sound economic conditions in the country where they are located in exhibit a reducing effect on systemic risk. Although we propose different measures for systemic risk, we empirically confirm the urgency of recent regulatory approaches to identify channels of contagion among banks in Europe by using a broad set of financial indicators (Basel Committee on Banking Supervision, 2013). Macroprudential regulation is essential to prevent systemic risk crises in the banking system.

Some limitations of our research, however, remain: Firstly, although our suggested copula-based model can be easily applied by practitioners, it is limited to the bivariate case, that is, each financial institution is only evaluated with respect to the whole banking system. Hence, it will be important to extend this analysis to the multivariate case where the connections among several individual institutions are simultaneously modelled. Moreover the use of CDS data excludes a high number of (admittedly “smaller”) institutions without publicly listed

CDS securities.¹⁷ The second shortfall is that we do not assess the contagious impact of other financial institutions, such as insurers, investment funds and players from the growing shadow banking system. Finally, to confirm our findings in the long run, future research could try to make use of financial and country data over longer periods.

¹⁷ The most useful measures of systemic risk may be ones that have yet to be tried because they require proprietary data only regulators can obtain (Bisias et al., 2012).

References

- Acemoglu, D., Ozdalgar, A., Tahbaz-Salehi, A., 2015. Systemic Risk and Stability in Financial Networks. *American Economic Review* 105, 564-608.
- Acharya, V., Bharath, S., Srinivasan, A., 2004. Understanding the Recovery Rates on Defaulted Securities, *Discussion Paper 4098, CEPR*, London.
- Acharya, V., Pedersen, L.H., Philippon, T., Richardson, M., 2011. Measuring Systemic Risk, *AFA 2011 Denver Meetings Paper*.
- Acharya, V., Steffen, S., 2014. Analyzing Systemic Risk of the European Banking Sector, in: Fouque/Langsam (ed.): *Handbook on Systemic Risk*, 37.
- Adrian, T., Brunnermeier, M.K., 2011. CoVaR. *NBER Working Papers* 17454.
- Bagehot, W., 1873. *Lombard Street: A description of the money market*, New York.
- Basel Committee on Banking Supervision, 2013. Global systemically important banks: updated assessment methodology and the higher loss absorbency requirement, Brussels.
- Berg, D., 2009. Copula goodness-of-fit testing: an overview and power comparison. *European Journal of Finance* 15 (7), 675-701.
- Billio, M., Getmansky, M., Lo, A.W., Pelizzon, L., 2012. Econometric measures of connectedness and systemic risk in the finance and insurance sectors. *Market Institutions, Financial Market Risks and Financial Crisis* 104 (3), 535-559. 10.1016/j.jfineco.2011.12.010.
- Bisias, D., Flood, M., Lo, A.W., Valavanis, S., 2012. A Survey of Systemic Risk Analytics. *Annu. Rev. Fin. Econ.* 4 (1), 255–296. 10.1146/annurev-financial-110311-101754.
- Black, L., Correa, R., Huang, X., Zhou, H., 2013. The Systemic Risk of European Banks During the Financial and Sovereign Debt Crisis, *International Finance Discussion Papers*, Board of Governors of the Federal Reserve System, Washington.
- Bluhm, C., Overbeck, L., Wagner, C., 2010. *Introduction to Credit Risk Modeling*, 2nd ed., London.
- Bori, N., Caccavaio, M., Di Giorgio, G., Sorrentino, A., 2012. Systemic risk in the European banking sector, *CASMEF Working Paper Series*, Rome.
- Brousseau, V., Chailloux, A., Durré, A., 2012. Fixing the Fixings: What Road to a More Representative Money Market Benchmark? *IMF Working Paper*.
- Brownlees, C., Engle, R., 2012. Volatility, Correlation And Tails For Systemic Risk Measurement, *Working Paper*.

- Brunnermeier, M., 2009. Deciphering The Liquidity And Credit Crunch 2007-2008. *Journal of Economic Perspectives* 23, 77-100.
- Buhler, W., Prokopczuk, M., 2010. Systemic Risk: Is the Banking Sector Special? *Working Paper*, Available at SSRN: <http://ssrn.com/abstract=1612683>.
- Casella, G., Berger, R., 2008. *Statistical inference*. Duxbury
- Chan-Lau, J. A., 2006. Market-Based Estimation of Default Probabilities and Its Application to Financial Market Surveillance, IMF Working Paper WP/06/104.
- Chan-Lau, J. A., 2010. Regulatory Capital Charges for Too-Connected-to-Fail Institutions: A Practical Proposal. *Financial Markets, Institutions & Instruments*, Vol. 19, No. 5, 355-379.
- Chan-Lau, J. A., 2013. *Systemic Risk Assessment and Oversight*. London: Risk Books.
- Conrad, J., Dittmar, R., Hameed, A., 2012. Cross-Market and Cross-Firm Effects in Implied Default Probabilities and Recovery Values, *AFA 2012 Chicago Meetings Paper*.
- Crouhy, M., Galai, D., Mark, R., 2014. *The Essentials of Risk Management*. McGraw Hill, Chapter 11.
- Czado, C., 2010. Pair-copula constructions for multivariate copulas. in: Jaworki et al. (eds.) *Workshop on Copula Theory and its Applications*. Dordrecht: Springer, 93-110.
- Dornbusch, R., Park, Y., Claessens, S. (2000). Contagion: Understanding how it spreads. *World Bank Research Observer* 15, 177-197.
- Driscoll, J., Kraay, A., 1998. Consistent Covariance Matrix Estimation with Spatially Dependent Panel Data. *Review of Economics and Statistics* 80 (4), 549-560.
- Duffie, Darrel J., 1999. Credit Swap Valuation, *Financial Analysts Journal* 55 (1), 73-87.
- Dungey, M., Luciani, M., Veredas, D., 2012. Ranking Systemically Important Financial Institutions. *Discussion Paper 2012-08*, School of Economics and Finance, University of Tasmania.
- Embrechts, P., McNeil, A., Strautman, D., 2002. Correlation and Dependency in Risk Management: Properties and Pitfalls. in: Dempster, M.A.H. (ed.) *“Risk Management: Value at Risk and Beyond”*. Cambridge, 176-223.
- Engle, R., Jondeau, E., Rockinger, M., 2014. Systemic risk in Europe. *Review of Finance*, 1-46.
- Flannery, M.J., Kwan, S.H., Nimalendran, M., 2013. The 2007–2009 financial crisis and bank opaqueness. *Research on the Financial Crisis* 22 (1), 55–84. 10.1016/j.jfi.2012.08.001.

- Genest, C., Rémillard, B., Beaudoin, D., 2009. Goodness-of-fit tests for copulas: A review and a power study. *Insurance: Mathematics and Economics* 44, 199-213.
- Grossmann, S., Shiller, R., 1981. The Determinants of the Variability of Stock Market Prices. *American Economic Review* 71 (2), 222-227.
- Hausmann, J., 1978. *Specification Tests in Econometrics*. *Econometrica* 46 (6), 1251–1271.
- Hautsch, N., Schaumburg, J., Schienle, M., 2014. Forecasting systemic impact in financial networks. *International Journal of Forecasting* 30 (3), 781–794. 10.1016/j.ijforecast.2013.09.004.
- Hou, D., Skeie, D., 2014. LIBOR: Origins, Economics, Crisis, Scandal, and Reform. *Federal Reserve Bank of New York Staff Reports*.
- Hull, J., White, A., 2000. Valuing Credit Default Swaps I: No Counterparty Default Risk, *Journal of Derivatives* 8, 29-40.
- Hull, J., White, A., 2013. LIBOR vs. OIS: The Derivatives Discounting Dilemma. *Journal of Investment Management* 11 (3), 14-27.
- Jankowitsch, R., Nagler, F., Subrahmanyam, M.G., 2014. The determinants of recovery rates in the US corporate bond market. *Journal of Financial Economics* 114 (1), 155-177. 10.1016/j.jfineco.2014.06.001.
- Jobst, A., Gray, D., 2013. Systemic Contingent Claims Analysis - Estimating Market-Implied Systemic Risk, *IMF Working Paper* 13/54.
- Joe, Harry, 2014. *Dependence Modeling with Copulas*. Chapman & Hall/CRC.
- JP Morgan, 1997. CreditMetrics Technical Document.
- KMV, 1987. Probability of Loss on Loan Portfolio, San Francisco.
- León, C., Murcia, A., 2013. Systemic Importance Index for Financial Institutions: A Principal Component Analysis approach, *ODEON* 7, 127-165.
- Martínez-Jaramillo, S., Pérez, O., Embriz, F., Dey, F., 2010. Systemic risk, financial contagion and financial fragility. *Journal of Economic Dynamics & Control* 34, 2358-2374.
- Mendonça, H., Galvão, D., Loures, R., 2013. Credit and bank opaqueness: How to avoid financial crises? *Economic Modelling* 33. 605–612. 10.1016/j.econmod.2013.05.001.
- Merton, R., 1974. On the Pricing of Corporate Debt: The Risk Structure of Interest Rates. *Journal of Finance* 28, 449-470.

- Morgan, D. P. Stiroh, K. J., 2005. "Too big to fail after all these years," *Staff Reports 220*, *Federal Reserve Bank of New York*.
- Nelsen, Roger B., 2006. *An Introduction to Copulas*. New York: Springer.
- Oh, D., Patton, A., 2013. Time-Varying Systemic Risk: Evidence from a Dynamic Copula Model of CDS Spreads. *Working Paper*.
- Perotti, E., Ratnovski, L., Vlahu, R., 2011. Capital Regulation and Tail Risk, *IMF Working Paper 11/188*.
- Philippas, D., Siriopoulos, C., 2013. Putting the "C" into crisis: Contagion, correlations and copulas on EMU bond markets. *Journal of International Financial Markets, Institutions and Money* 27, 161-176.
- Sarbu, S., Schmitt, C., Uhrig-Homburg, M., 2013. Market expectations of recovery rates, *Working paper Karlsruhe Institute of Technology*, Karlsruhe.
- Vallascas, F., Keasey, K., 2012. Bank resilience to systemic shocks and the stability of banking systems: Small is beautiful. *Journal of International Money and Finance* 31 (6), 1745–1776. 10.1016/j.jimonfin.2012.03.011.
- Varotto, S., Zhao, L., 2014. Systemic Risk in the US and European Banking Sectors, *Working Paper ICMA Centre*, Reading.
- Wei, G., Bostandzic, D., Neumann, S., 2014. What factors drive systemic risk during international financial crises? *Journal of Banking & Finance* 41, 78–96. 10.1016/j.jbankfin.2014.01.001

Table 1: Illustrative data on series of copulas representing a bank's probability of default conditional on the banking system's default

This table provides hypothetical data concerning the default probability of a bank at time t ($PD_{bank,t}$) and the probability of distress in the banking system at time t ($PD_{system,t}$).

Month	PD_{bank}	PD_{system}	Conditional PD	
			In copula notation	Using data from PD_{bank} and PD_{system}
1	0.02	0.03	$C(PD_{bank,1}, PD_{system,1}) / PD_{system,1}$	$[C(0.02,0.03)]/0.03$
2	0.02	0.04	$C(PD_{bank,2}, PD_{system,2}) / PD_{system,2}$	$[C(0.02,0.04)]/0.04$
3	0.03	0.07	$C(PD_{bank,3}, PD_{system,3}) / PD_{system,3}$	$[C(0.03,0.07)]/0.07$
...
T	0.03	0.06	$C(PD_{bank,T}, PD_{system,T}) / PD_{system,T}$	$[C(0.03,0.06)]/0.06$

Table 2: Number of best-fit copulas (between financial institutions' PD and banking system's PD)

This table provides the number of cases where the dependence between banks' PD and the banking system's PD is represented by each of the copulas tested.

Copula	Number of banks
Clayton	30
Gaussian	0
Gumbel	4
Student t	13
Total	47

Table 3. Summary statistics for bank characteristics and country controls

This table provides descriptive statistics for bank-specific financial data (from balance sheets and profit and loss statements) and country controls used in the panel regressions. Bank-specific data are taken from the databases *Thomson Worldscope* and *Thomson Reuters Financial Datastream*. Country controls come from the *World Bank* or the *Eurostat* database. Further variable definitions and data sources are provided in Appendix Table 2.

Explanatory variable	Expected influence	Symbol	Obs	Mean	Median	Std.dev.	Min	Max
<i>Non-performing loan ratio</i>	+	<i>NON_PERF</i>	260	0.94%	0.68%	0.95%	-0.15%	7.63%
<i>Tier 1 ratio</i>	+/-	<i>TIER1</i>	260	10.18%	10.00%	3.15%	-6.70%	21.40%
<i>Deposit ratio</i>	+/-	<i>DEPOSIT</i>	260	40.41%	40.45%	12.49%	6.30%	67.90%
<i>Leverage ratio</i>	+	<i>LEVERAGE</i>	260	8.16	7.15	12.87	-93.6	99.7
<i>Liquidity ratio</i>	-	<i>LIQUIDITY</i>	260	108.63%	70.65%	86.38%	20.50%	712.80%
<i>Return on invested capital</i>	+/-	<i>ROIC</i>	260	1.58%	2.10%	3.15%	-29.40%	11.60%
<i>Government debt</i>	+	<i>DEBT</i>	260	81.22%	81.60%	34.05%	20.60%	174.90%
<i>Bank claims to government</i>	+	<i>CLAIM</i>	260	18.08%	17.90%	12.06%	-12.40%	44.80%
<i>Bank credits to private</i>	+	<i>CREDIT</i>	260	135.26%	120.00%	44.59%	0.00%	224.00%
<i>State aid dummy</i>	+/-	<i>AID</i>	260	7.70%	0.00%	26.70%	0.00%	100%

Table 4: Summary statistics for systemic risk sensitivity: PDbank/system

This table provides average systemic risk sensitivity of the sample analysed in each year considered and other related statistics for the whole period. Recovery rate refers to the values used to estimate PD according to [5]. The table presents the information for each year in our sample period and the results aggregated for the whole period.

Recovery rate	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2005 - 2014				
											Mean	Median	Std.dev.	Min	Max
10%	0.735	0.754	0.737	0.624	0.584	0.627	0.602	0.589	0.620	0.627	0.637	0.638	0.253	0.088	1.000
40%	0.737	0.756	0.740	0.628	0.588	0.631	0.606	0.594	0.626	0.634	0.641	0.643	0.250	0.106	1.000
50%	0.738	0.757	0.741	0.630	0.590	0.634	0.609	0.597	0.629	0.638	0.644	0.647	0.248	0.115	1.000
60%	0.740	0.759	0.742	0.632	0.593	0.636	0.612	0.600	0.633	0.643	0.647	0.648	0.246	0.127	1.000
90%	0.749	0.769	0.754	0.652	0.617	0.662	0.639	0.633	0.668	0.643	0.668	0.667	0.235	0.203	1.000

Table 5: Summary statistics for systemic risk contribution: PDsystem/bank

This table provides average systemic risk sensitivity of the sample analysed in each year considered and other related statistics for the whole period. Recovery rate refers to the values used to estimate PD according to [5]. The table presents the information for each year in our sample period and the results aggregated for the whole period.

Recovery rate	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2005 - 2014				
											Mean	Median	Std.dev.	Min	Max
10%	0.795	0.779	0.803	0.824	0.737	0.696	0.703	0.695	0.669	0.653	0.722	0.765	0.226	0.166	0.999
40%	0.798	0.782	0.806	0.829	0.742	0.702	0.710	0.703	0.678	0.663	0.728	0.771	0.221	0.199	0.999
50%	0.799	0.783	0.807	0.832	0.745	0.705	0.713	0.707	0.682	0.668	0.731	0.774	0.219	0.202	0.999
60%	0.801	0.785	0.809	0.835	0.747	0.707	0.715	0.710	0.685	0.672	0.734	0.783	0.220	0.166	0.999
90%	0.811	0.796	0.822	0.862	0.783	0.744	0.758	0.760	0.742	0.744	0.774	0.808	0.198	0.202	0.999

Table 6. Panel regressions (random effects) of banks' systemic risk for a recovery ratio of 50%

The table presents the results of the panel regression (random effects) of banks' systemic risk on the European banking sector. For the estimation of the linear panel regression model, we use heteroskedasticity-robust Huber-White standard errors. The p-values are denoted in parentheses. */**/** indicate coefficient significance at the 10%/5%/1% level. Variable definitions and sources are provided in Appendix Table 2.

Dependent variable: Recovery rate:		<i>Systemic risk sensitivity</i> $PD_{bank/system}$ RR: 50%		<i>Systemic risk contribution</i> $PD_{system/bank}$ RR: 50%	
		<i>Tranquil</i> 2005-2007	<i>Crisis</i> 2008-2013	<i>Tranquil</i> 2005-2007	<i>Crisis</i> 2008-2013
<i>Non-performing loan ratio</i>	<i>NON_PERF</i>	-6.287 (0.106)	0.681 (0.388)	10.901* (0.050)	-0.527 (0.398)
<i>Tier 1 ratio</i>	<i>TIER1</i>	-1.020 (0.319)	-0.361* (0.062)	1.990* (0.085)	0.194 (0.428)
<i>Deposit ratio</i>	<i>DEPOSIT</i>	-0.177 (0.539)	0.248** (0.036)	0.115 (0.741)	-0.054 (0.738)
<i>Leverage ratio</i>	<i>LEVERAGE</i>	-0.246 (0.628)	-0.022 (0.111)	0.332 (0.586)	-0.009 (0.444)
<i>Liquidity ratio</i>	<i>LIQUIDITY</i>	-0.008 (0.632)	0.059** (0.017)	-0.003 (0.904)	-0.024* (0.093)
<i>Return on invested capital</i>	<i>ROIC</i>	1.932* (0.090)	0.241 (0.125)	-1.726 (0.173)	-0.149 (0.249)
<i>Government debt</i>	<i>DEBT</i>	1.017*** (0.001)	0.208*** (0.002)	-0.821** (0.012)	-0.367** (0.013)
<i>Bank claims to government</i>	<i>CLAIM</i>	-0.629* (0.060)	0.306** (0.034)	0.661* (0.078)	0.072 (0.665)
<i>Bank credits to private</i>	<i>CREDIT</i>	0.106** (0.033)	0.303*** (0.001)	-0.017 (0.809)	-0.087 (0.318)
<i>State aid dummy</i>	<i>AID</i>	- (0.002)	-9.833*** (0.002)	- (0.023)	6.136** (0.023)
<i>Observations</i>		64	196	64	196
<i>Groups</i>		22	36	22	36
<i>R²</i>		within 0.424	within 0.433	within 0.366	within 0.373

Figure 1. Systemic risk contribution and sensitivity

This figure illustrates the two different contagion channels of systemic risk. Systemic risk sensitivity refers to a overall (macroeconomic) shock (change of a lead interest rate) that negatively affects each single financial institution. Systemic risk contribution refers to an individual shock in one bank (e.g. the default of an important borrower) that is transmitted into the whole banking system.

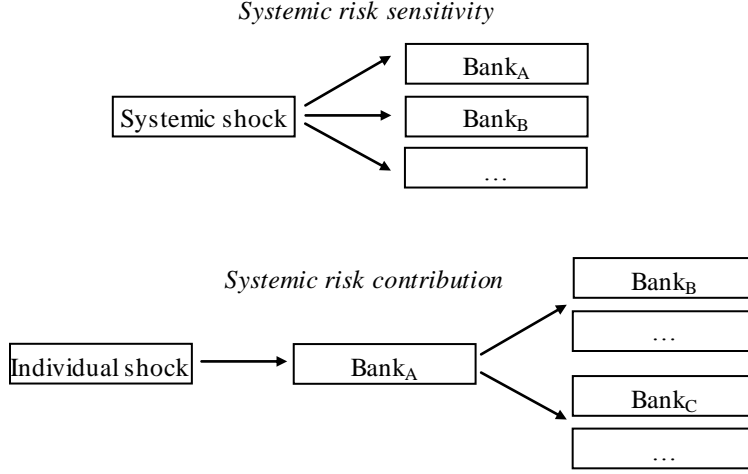


Figure 2. The probability of default according to the interpretation of structural models.

This diagram represents the probability of default (PD) in terms of the density function of a latent variable assumed to drive default. Default happens whenever the underlying variable (Y) falls below a cut-off point (y_c). The probability of default is given by the area on the left-hand side of the cut-off point.

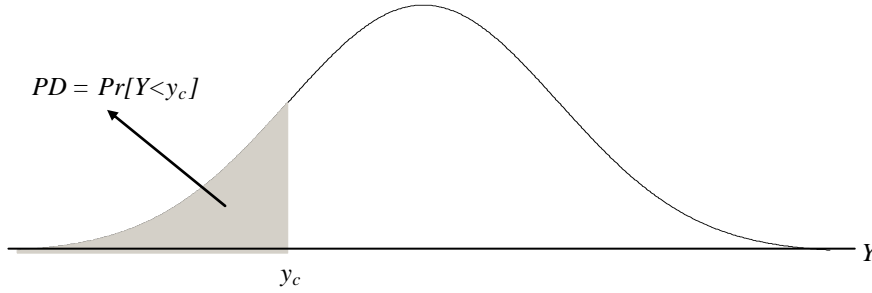
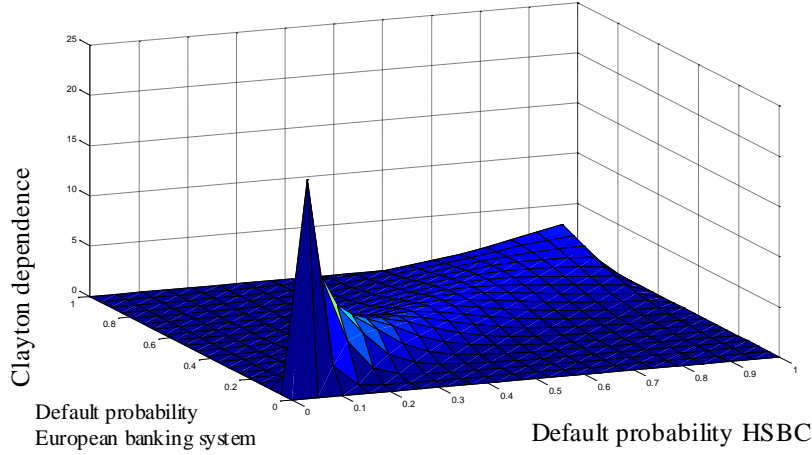


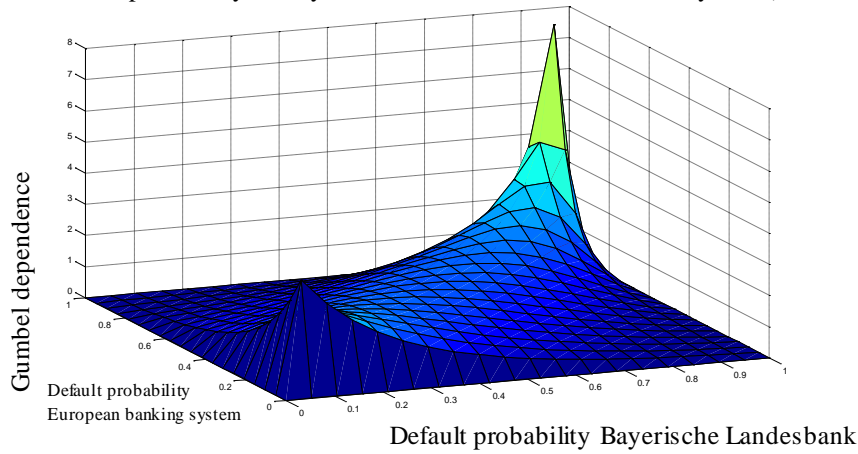
Figure 3: Diagram representing three different dependence structures between the bank system's risk and the risk of selected banks in our sample.

This diagram illustrates the dependence between the risk of the bank system and the risk of three banks in our sample: Credit Agricole (Student t dependence), Bayerische Landesbank (Gumbel dependence), and HSBC (Clayton dependence), respectively.

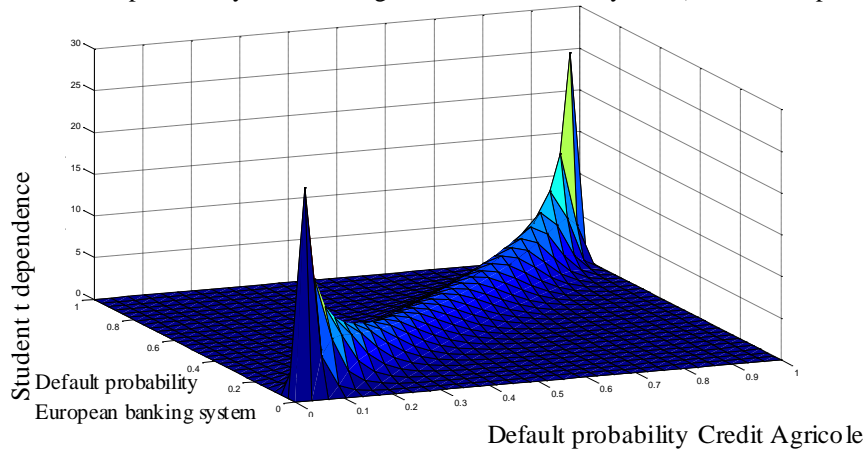
Joint default probability of HSBC and the bank system (Clayton dependence)



Joint default probability of Bayerische Landesbank and the bank system (Gumbel dependence)



Joint default probability of Credit Agricole and the bank system (Student t dependence)



Appendix

Appendix Table 1. Bank sample constituents

The table provides the full list of banks in the sample including the names of the countries where the respective bank is headquartered in.

Country	Bank name		
AUT	Erste Group AG	GRE	National Bank of Greece SA
BUK	KBC Group NV	GRE	Eurobank Ergasias SA
BUL	Dexia NV	IRL	Allied Irish Banks plc
DES	Danske Bank	IRL	Bank of Ireland
ESP	BBVA SA	ITA	B. Monte dei Paschi di Siena SpA
ESP	Banco de Sabadell SA	ITA	Banca Popolare Di Milano SC
ESP	Banco Popular Español SA	ITA	Banco Popolare SC
ESP	Banco Santander SA	ITA	Intesa Sanpaolo SpA
ESP	Bankinter SA	ITA	Mediobanca SpA
FRA	Groupe Crédit Agricole	ITA	UniCredit SpA
FRA	Société Générale	ITA	Unione Di Banche Italiane SpA
GBR	Lloyds Banking Group plc	NED	ING Bank N.V.
GBR	Barclays plc	NOR	DNB A/S
GBR	HSBC Holdings plc	POR	Banco Comercial Português SA
GER	Commerzbank AG	SWE	Nordea AB (publ)
GER	Deutsche AG	SWE	Skandinaviska Enskilda B. AB (SEB)
GER	IKB Deutsche Industriebank AG	SWE	Svenska Handelsbanken AB (publ)
GRE	Alpha Bank SA	SWE	Swedbank AB (publ)

Appendix Table 2. Definitions and data sources of explanatory variables

The table provides definitions and data sources for the variables used in the panel regressions.

Variable	Symbol	Definition	Data source
<i>Dependent variable</i>			
Systemic risk sensitivity	$PD_{bank/system}$	For detailed definition see Section 3. $PD_{bank/system}$ measures systemic risk of banks as the probability of default of an individual bank conditional on a systemic crisis in the banking system.	Own calculations with daily CDS data from S&P Capital IQ
Systemic risk contribution	$PD_{system/bank}$	For detailed definition see Section 3. $PD_{system/bank}$ measures systemic risk of the banking system as the probability of default of the banking system conditional on an individual negative shock for a bank.	Own calculations with daily CDS data from S&P Capital IQ
<i>Independent variables bank characteristics</i>			
Non-performing loan ratio	NON_PERF	$\frac{\text{Loan loss provisions}}{\text{Total loans}}$	WC01271, WC02271
Tier 1 ratio	$TIER1$	$\frac{\text{Basel III Tier 1 capital}}{\text{Risk-weighted assets}}$	WC18157
Deposit ratio	$DEPOSIT$	$\frac{\text{Total deposits}}{\text{Total liabilities}}$	WC03019, WC03351
Leverage ratio	$LEVERAGE$	$\frac{\text{Long + short term debt \& current portion of long term debt}}{\text{Common equity}}$	WC08231
Liquidity ratio	$LIQUIDITY$	$\frac{\text{Cash \& securities}}{\text{Deposits}}$	WC15013
Return on invested capital	$ROIC$	$\frac{\frac{\text{Net income - bottom line + (interest expense on debt - interest capitalized)} \times (1 - \text{Tax Rate})}{\text{Average of last and current year's invested capital}}}{(\text{total capital} + \text{short term debt} - \text{current Portion of Long Term Debt})}$	WC08376
<i>Independent variables macro and policy controls</i>			
Government debts	$DEBT$	The indicator is defined (in the Maastricht Treaty) as consolidated general government gross debt at nominal value, outstanding at the end of the year. All values are scaled with the respective GDP.	Eurostat tsdde410
Bank claims to government	$BANK_CL$	Banks' claims on central government as a percentage of GDP include loans to central government institutions net of deposits.	World Development Indicators FS.AST.CGOV.GD.ZS
Bank credits to private	$CREDIT$	Financial resources provided to the private sector by depository corporations (deposit taking corporations except central banks), such as through loans, purchases of nonequity securities, and trade credits and other accounts receivable, that establish a claim for repayment (% of GDP).	World Development Indicators FD.AST.PRVT.GD.ZS
State aid dummy	AID	Dummy variable that becomes 1 if a bank receives any advantage in any form whatsoever conferred on a selective basis to undertakings by national public authorities.	European Commission competition case database http://ec.europa.eu/competition/eojade/isef/index.cfm

Appendix Table 3. Panel data tests/diagnostics

The table provides results of five tests for time fixed/random effects and cross sectional dependence for the panel regressions in Table 6.

Test/diagnostic		<i>Systemic risk sensitivity</i>		<i>Systemic risk contribution</i>	
		<i>PD_{bank/system_50%}</i>		<i>PD_{system/bank_50%}</i>	
Dependent variable:		<i>Tranquil</i> <i>2005-2007</i>	<i>Crisis</i> <i>2008-2013</i>	<i>Tranquil</i> <i>2005-2007</i>	<i>Crisis</i> <i>2008-2013</i>
Random effects:					
LM-test	Prob>chi ² =	0.000	0.000	0.000	0.000
Hausman-test	Prob>chi ² =	0.690	-	-	0.000
Time fixed effects	Prob>F=	0.712	0.000	0.407	0.000
Cross sectional dependence:		We use Driscoll and Kraay (1998) standard error estimates to account for cross sectional dependence, auto-correlation and heteroskedasticity.			
Autocorrelation:					
Heteroskedasticity:					

Appendix Table 4: Correlation matrix

The table provides the correlations of the variables used in the panel regressions. Variable definitions and sources are provided in Appendix Table 2. As in our baseline regressions, $PD_{system|bank}$ and $PD_{bank|system}$ are calculated by assuming recovery rate (RR) equal to 0.50.

	$PD_{bank system}$	$PD_{system bank}$	NON_PERF	$TIER1$	$DEPOSIT$	$LEVERAGE$	$LIQUIDITY$	$ROIC$	$DEBT$	$CLAIM$	$CREDIT$	AID
$PD_{bank system}$	1											
$PD_{system bank}$	-0.26***	1										
NON_PERF	0.37***	-0.38***	1									
$TIER1$	-0.22***	0.05	0.03	1								
$DEPOSIT$	0.25***	-0.33***	0.34***	-0.09	1							
$LEVERAGE$	-0.03	0.04	-0.18***	0.08	-0.25***	1						
$LIQUIDITY$	-0.10	0.40***	-0.21***	0.21***	-0.74***	0.13**	1					
$ROIC$	-0.26***	0.36***	-0.49***	0.16***	-0.10	0.14**	0.13**	1				
$DEBT$	0.61***	-0.22***	0.44***	0.02	0.27***	-0.19***	-0.11*	-0.43***	1			
$CLAIM$	0.39*	0.12*	0.16**	0.06	0.09	-0.08	-0.01	-0.24***	0.71***	1		
$CREDIT$	0.01	-0.10*	0.30***	0.04	0.19***	-0.00	-0.17***	0.02	-0.29***	-0.26***	1	
AID	-0.01	0.19***	-0.12	0.20***	-0.21***	0.01	0.17***	-0.02	0.05	0.04	-0.20***	1

*/**/*** statistically significant at the 10%/5%/1% level.

Appendix Table 5: Panel regressions (fixed effects) of banks' systemic risk for a recovery ratio of 10% and 90%

The table presents the results of the panel regression (fixed effects) of banks' systemic risk on the European banking sector. For the estimation of the linear panel regression model, we use heteroskedasticity-robust Huber-White standard errors. The p-values are denoted in parentheses. */**/** indicate coefficient significance at the 10%/5%/1% level. Variable definitions and sources are provided in Appendix Table 2.

Dependent variable:		<i>Systemic risk sensitivity</i>		<i>Systemic risk contribution</i>	
		<i>PD_{bank/system}</i>		<i>PD_{system/bank}</i>	
Recovery rate:		RR: 10%		RR: 10%	
		<i>Tranquil</i>	<i>Crisis</i>	<i>Tranquil</i>	<i>Crisis</i>
		<i>2005-2007</i>	<i>2008-2013</i>	<i>2005-2007</i>	<i>2008-2013</i>
<i>Non-performing loan ratio</i>	<i>NON_PERF</i>	-6.205 (0.112)	0.683 (0.382)	10.853** (0.046)	-0.497 (0.417)
<i>Tier 1 ratio</i>	<i>TIER1</i>	-1.030 (0.314)	-0.362* (0.061)	1.988* (0.083)	0.179 (0.458)
<i>Deposit ratio</i>	<i>DEPOSIT</i>	-0.181 (0.530)	0.244** (0.039)	0.110 (0.750)	-0.060 (0.706)
<i>Leverage ratio</i>	<i>LEVERAGE</i>	-0.259 (0.609)	-0.022 (0.119)	0.329 (0.586)	-0.008 (0.488)
<i>Liquidity ratio</i>	<i>LIQUIDITY</i>	-0.008 (0.630)	0.058** (0.018)	-0.002 (0.906)	-0.024* (0.080)
<i>Return on invested capital</i>	<i>ROIC</i>	1.929* (0.090)	0.238 (0.126)	-1.722 (0.172)	-0.144 (0.260)
<i>Government debt</i>	<i>DEBT</i>	1.010*** (0.001)	0.206*** (0.003)	-0.816** (0.012)	-0.365** (0.012)
<i>Bank claims to government</i>	<i>CLAIM</i>	-0.631* (0.059)	0.299** (0.039)	0.657* (0.078)	0.065 (0.692)
<i>Bank credits to private</i>	<i>CREDIT</i>	0.102** (0.038)	0.302*** (0.001)	-0.022 (0.752)	-0.090 (0.297)
<i>State aid dummy</i>	<i>AID</i>	- (0.002)	-9.725*** (0.002)	- (0.002)	6.186** (0.020)
<i>Observations</i>		64	196	64	196
<i>Groups</i>		22	36	22	36
<i>R²</i>		within 0.425	within 0.428	within 0.365	within 0.381

Appendix Table 6: Panel regressions (fixed effects) of banks' systemic risk for a recovery ratio of 90%

The table presents the results of the panel regression (fixed effects) of banks' systemic risk on the European banking sector. For the estimation of the linear panel regression model, we use heteroskedasticity-robust Huber-White standard errors. The *p*-values are denoted in parentheses. */**/** indicate coefficient significance at the 10%/5%/1% level. Variable definitions and sources are provided in Appendix Table 2.

Dependent variable:		Systemic risk sensitivity		Systemic risk contribution	
		$PD_{bank/system}$		$PD_{system/bank}$	
Recovery rate:		RR: 90%		RR: 90%	
		Tranquil	Crisis	Tranquil	Crisis
		2005-2007	2008-2013	2005-2007	2008-2013
<i>Non-performing loan ratio</i>	<i>NON_PERF</i>	-6.609* (0.091)	0.590 (0.464)	11.017* (0.065)	-0.743 (0.318)
<i>Tier 1 ratio</i>	<i>TIER1</i>	-0.993 (0.331)	-0.334* (0.091)	1.998* (0.095)	0.286 (0.296)
<i>Deposit ratio</i>	<i>DEPOSIT</i>	-0.164 (0.573)	0.282** (0.021)	0.131 (0.713)	0.004 (0.981)
<i>Leverage ratio</i>	<i>LEVERAGE</i>	-0.199 (0.695)	-0.027* (0.075)	0.346 (0.581)	-0.016 (0.238)
<i>Liquidity ratio</i>	<i>LIQUIDITY</i>	-0.008 (0.634)	0.060** (0.021)	-0.003 (0.890)	-0.019 (0.220)
<i>Return on invested capital</i>	<i>ROIC</i>	1.941* (0.091)	0.239 (0.153)	-1.752 (0.179)	-0.198 (0.176)
<i>Government debt</i>	<i>DEBT</i>	1.038*** (0.000)	0.210*** (0.001)	-0.839** (0.015)	-0.384** (0.016)
<i>Bank claims to government</i>	<i>CLAIM</i>	-0.620* (0.064)	0.345** (0.016)	0.677* (0.078)	0.105 (0.563)
<i>Bank credits to private</i>	<i>CREDIT</i>	0.121** (0.020)	0.319*** (0.000)	0.001 (0.985)	-0.066 (0.475)
<i>State aid dummy</i>	<i>AID</i>	- (0.001)	-10.423*** (0.001)	- (0.001)	5.577* (0.058)
<i>Observations</i>		64	196	64	196
<i>Groups</i>		22	36	22	36
<i>R²</i>		within 0.430	within 0.443	within 0.369	within 0.329